LANDSLIDE PREDICTION USING DEEP LEARNING

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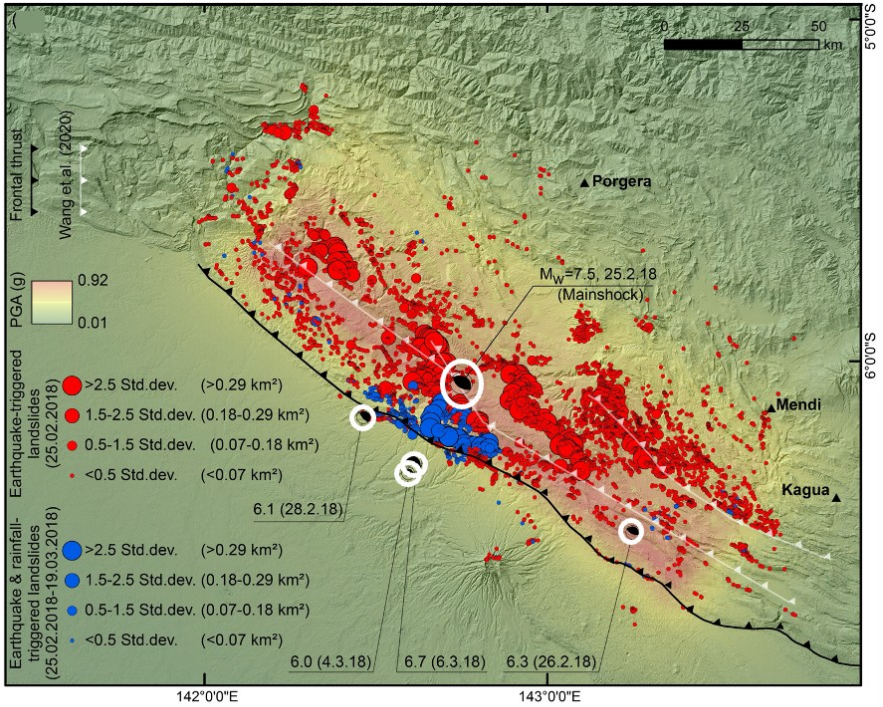
Outline

- Introduction
- Objectives
- Methodology
- Results
- Discussion and conclusion

Introduction: Earthquake induced landslides

- Based on the 2018 earthquake in Papua New guinea.
- 11000 landslides recorded in the inventory.
- Resulted in some of the largest landslides ever recorded.



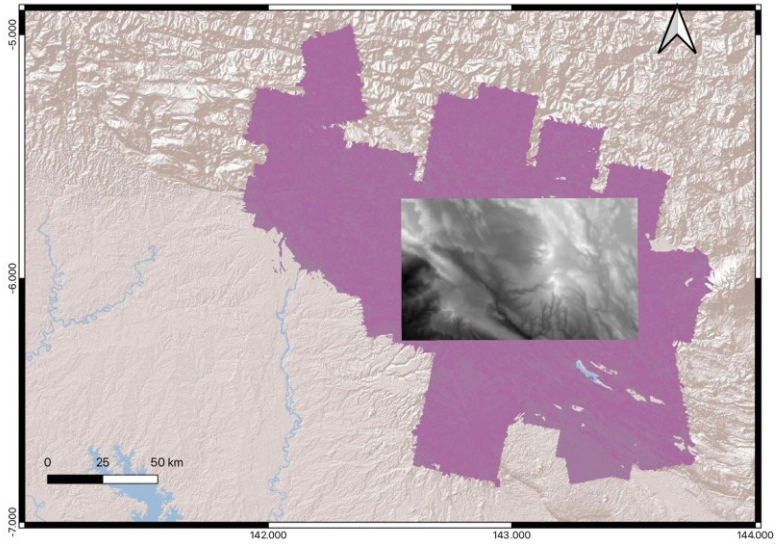
(Adapted from Tanyas et al., 2022)

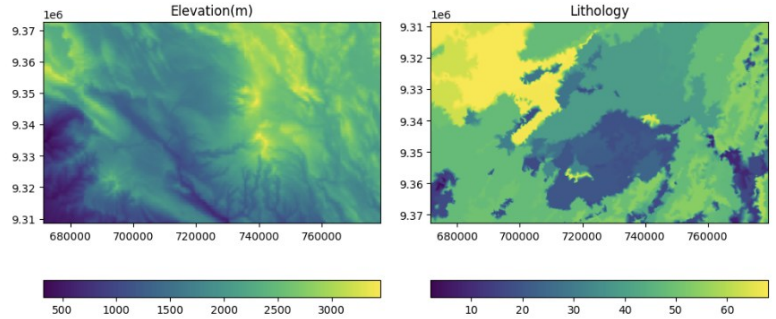
Objectives

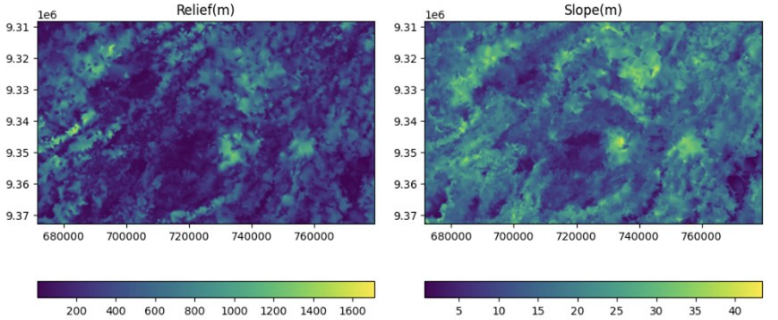
Conduct landslide prediction using deep learning methods:

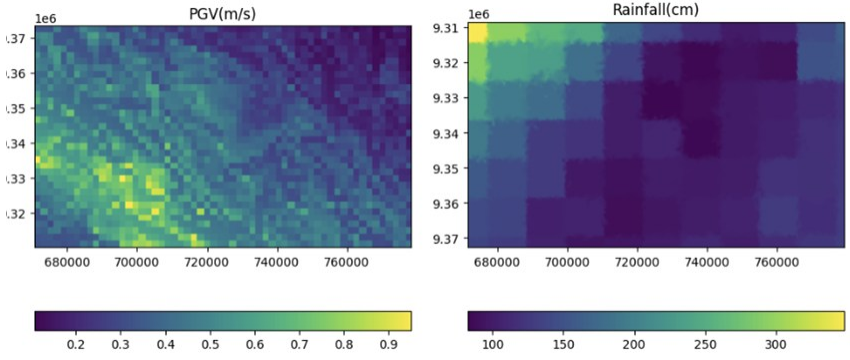
- Prediction using UNet and R2-UNet.
- Comparison of performance of the models.

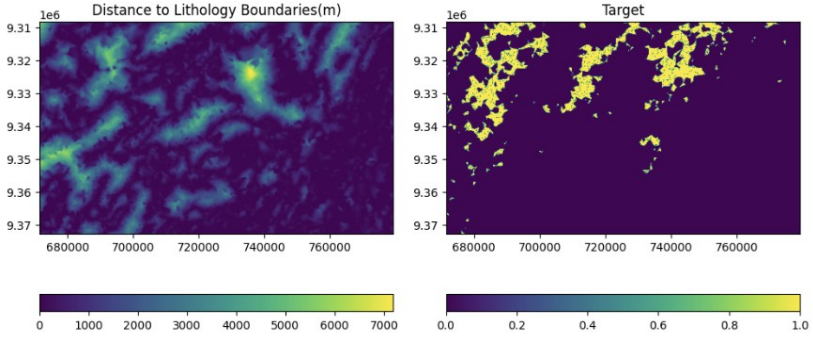
Data


-5.000
-6.000
-7.000
142.000
143.000
144.000
0
25
50 km

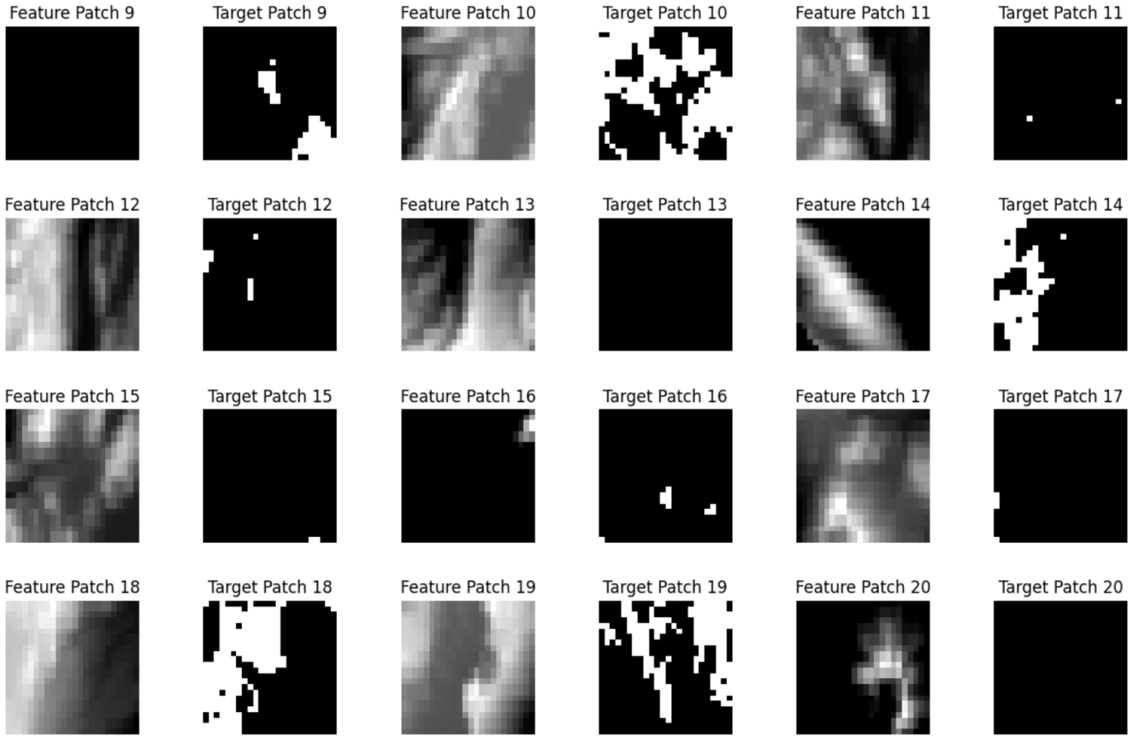

Elevation(m)
Lithology
1e6
9.37
9.36
9.35
9.34
9.33
9.32
9.31
680000
700000
720000
740000
760000
500
1000
1500
2000
2500
3000
10
20
30
40
50
60


Relief(m)
Slope(m)
1e6
9.31
9.32
9.33
9.34
9.35
9.36
9.37
680000
700000
720000
740000
760000
200
400
600
800
1000
1200
1400
1600
5
10
15
20
25
30
35
40


PGV(m/s)
Rainfall(cm)
1e6
9.37
9.36
9.35
9.34
9.33
9.32
9.31
680000
700000
720000
740000
760000
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
100
150
200
250
300

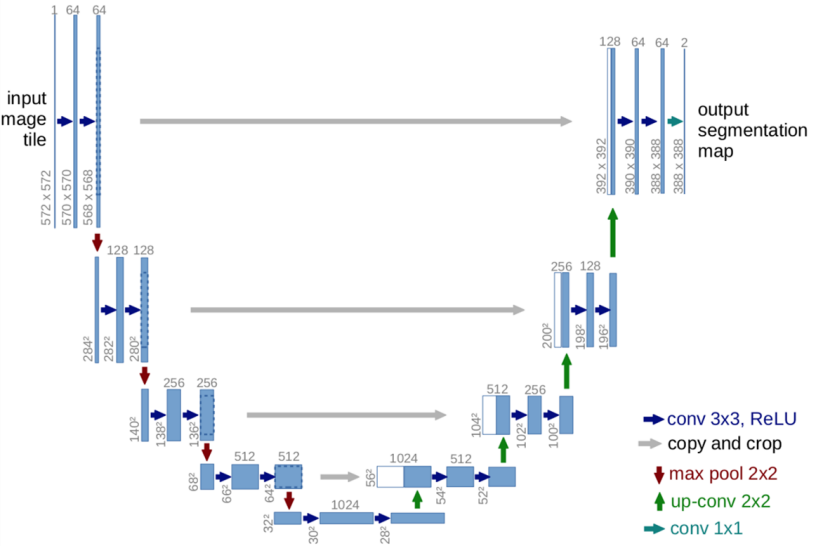

Distance to Lithology Boundaries(m)
Target
1e6
9.37
9.36
9.35
9.34
9.33
9.32
9.31
680000
700000
720000
740000
760000
0
1000
2000
3000
4000
5000
6000
7000
0.0
0.2
0.4
0.6
0.8
1.0

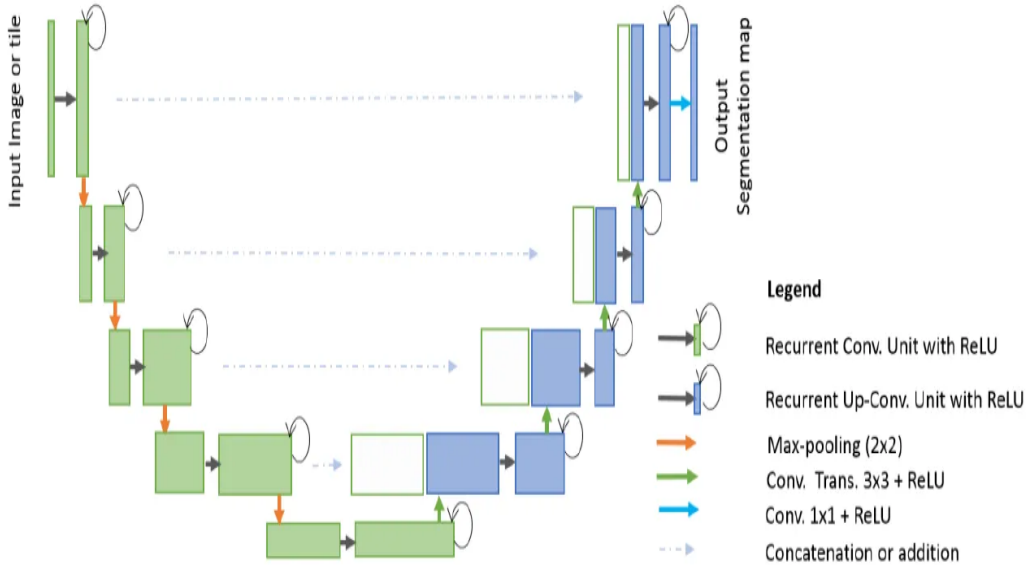
Data



- The .tiff files were split into patches.
- Augmentation: Vertical and Horizontal flip

Methodology: Models

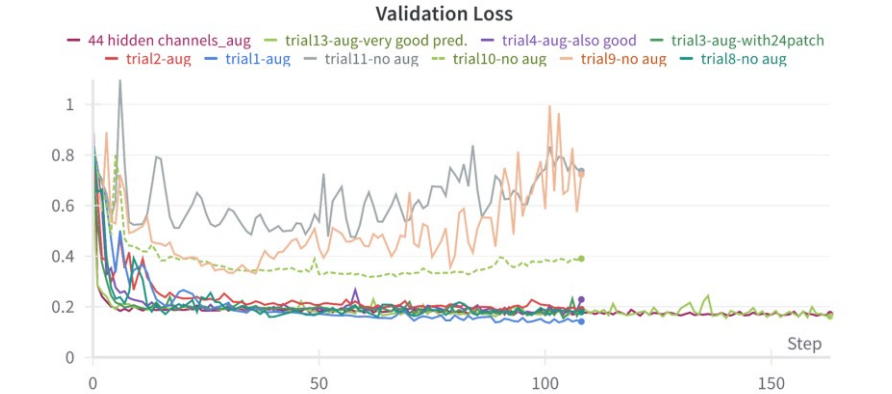




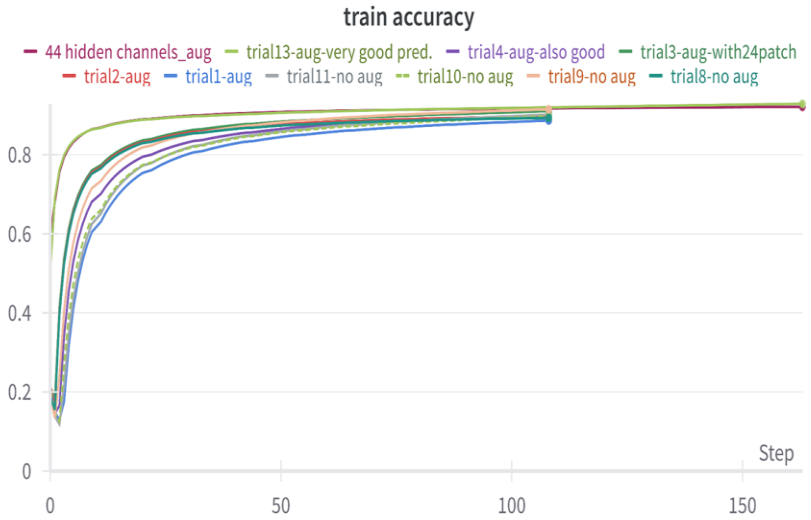
- R2Unet incorporates the properties of both RNN and ResNet into the UNet.
- The skip connections enable the training of deeper networks.
- The recurrent units improves the network's capacity for feature extraction.

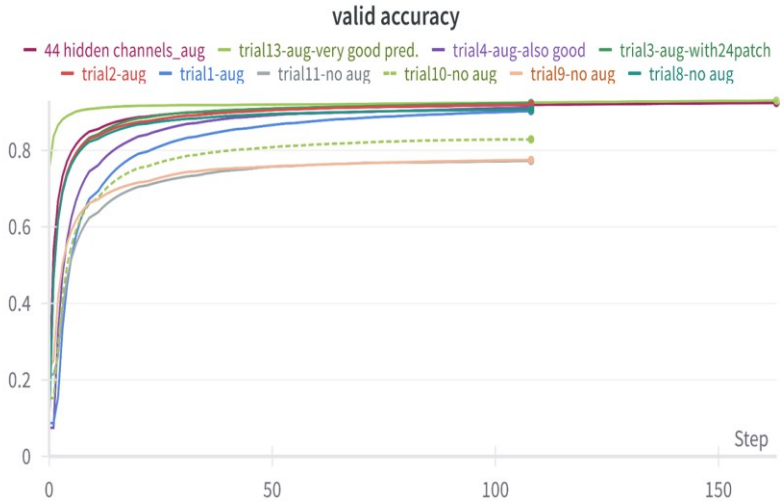
Methodology: Hyper-parameter Tuning

Name	batch_size	hidden_channels	lr	patch_size
44 hidden channels_aug	32	44	0.001	[24,24]
trial13-aug-very good pred.	32	32	0.001	[24,24]
trial4-aug-also good	64	16	0.001	[24,24]
trial3-aug-with24patch	32	16	0.001	[24,24]
trial2-aug	32	16	0.001	[32,32]
trial1-aug	32	16	0.001	[64,64]
trial11-no aug	32	16	0.001	[64,64]
trial10-no aug	32	16	0.001	[32,32]
trial9-no aug	32	16	0.001	[24,24]
trial8-no aug	32	16	0.001	[16,16]



Methodology: Hyper-parameter Tuning

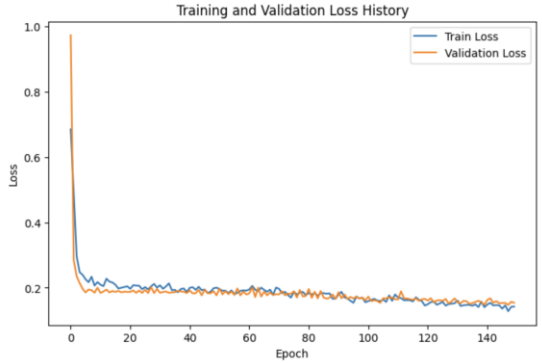


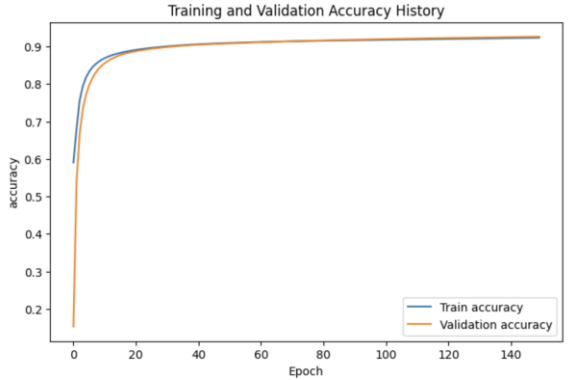


The parameters we used that we found appropriate for the final training “patch_size": (24,24), "batch_size": 32, "hidden_channels": 44 for U-Net and 64 for R2U-Net, "lr": 0.001, "weight_decay": 0.001, "epochs": 150.

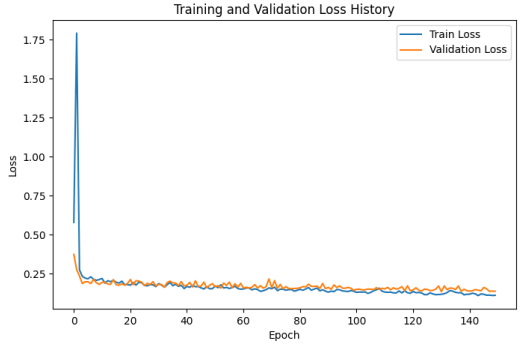
Results

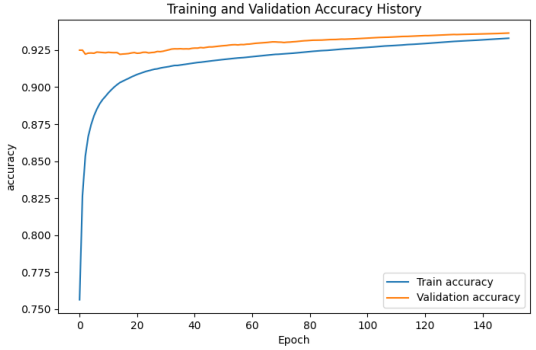
UNet





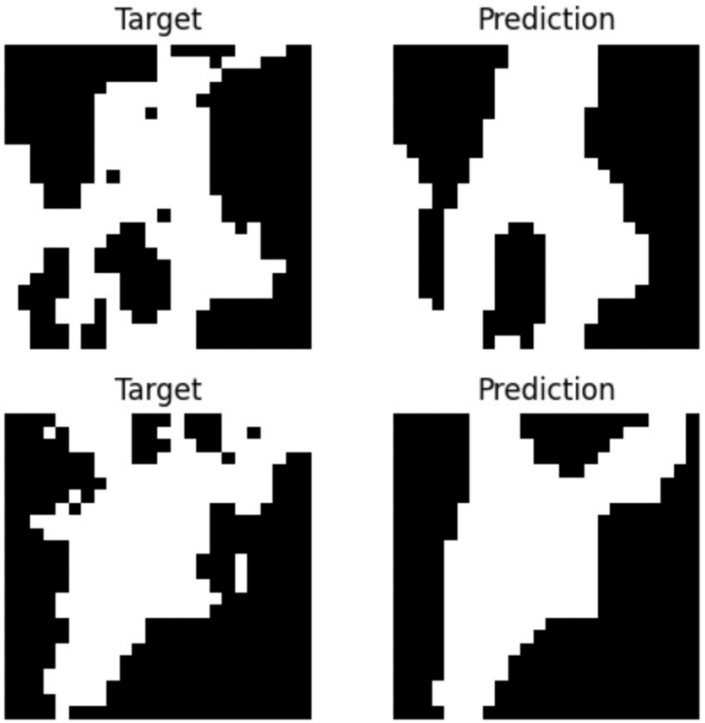
R2U-Net



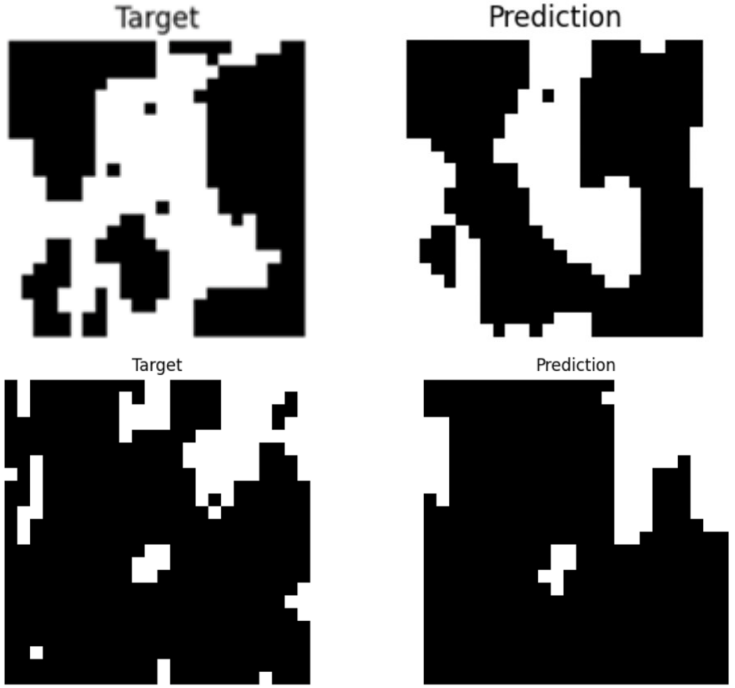


Results

UNet

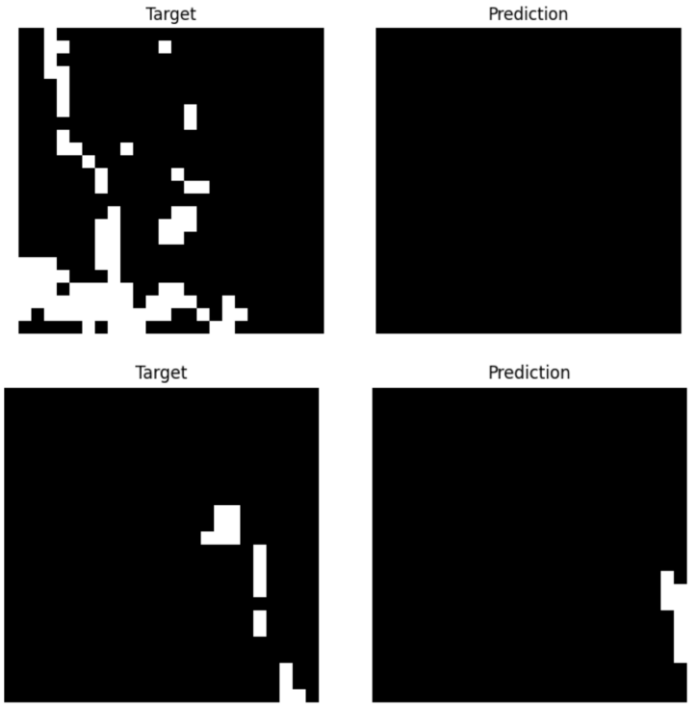


R2U-Net

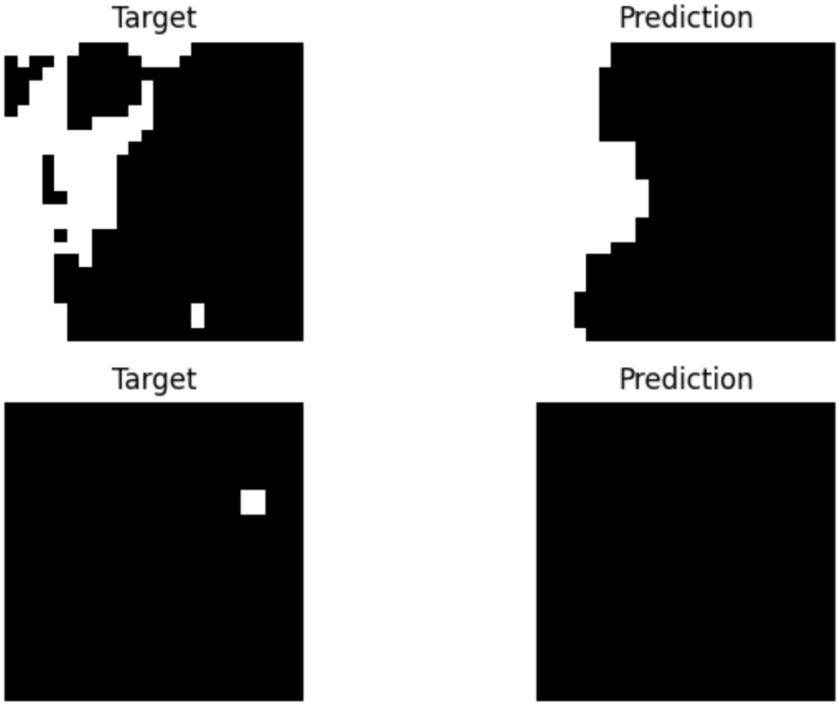


Results

UNet

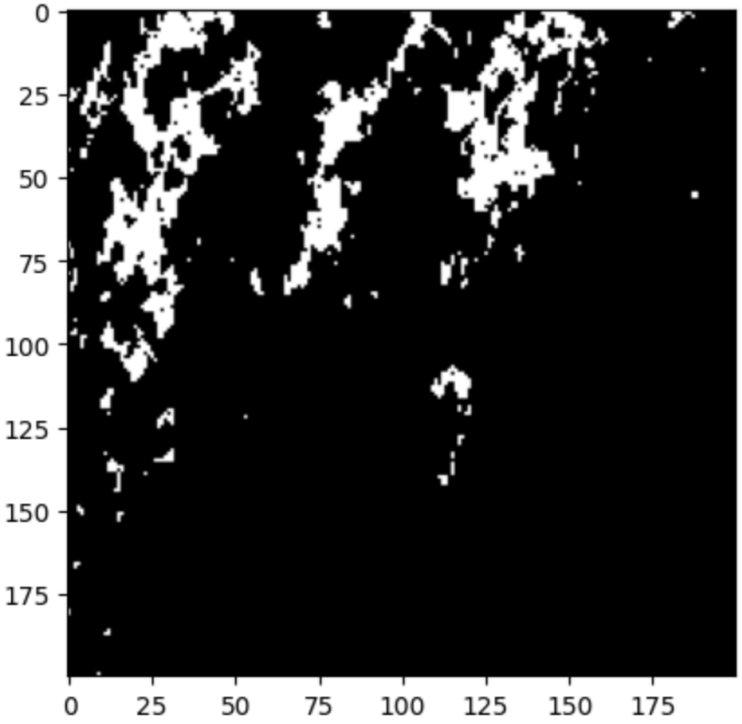


R2U-Net

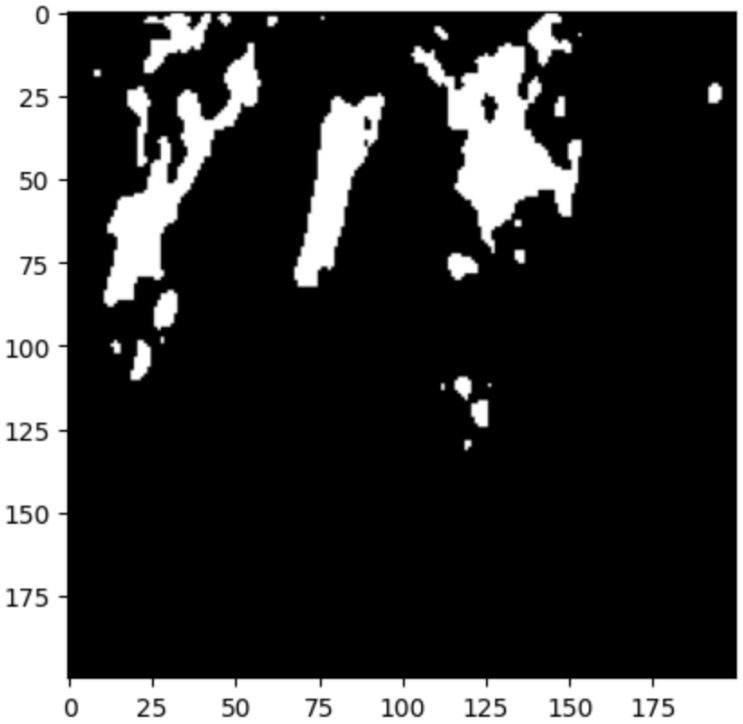


Results

Entire Area as Target

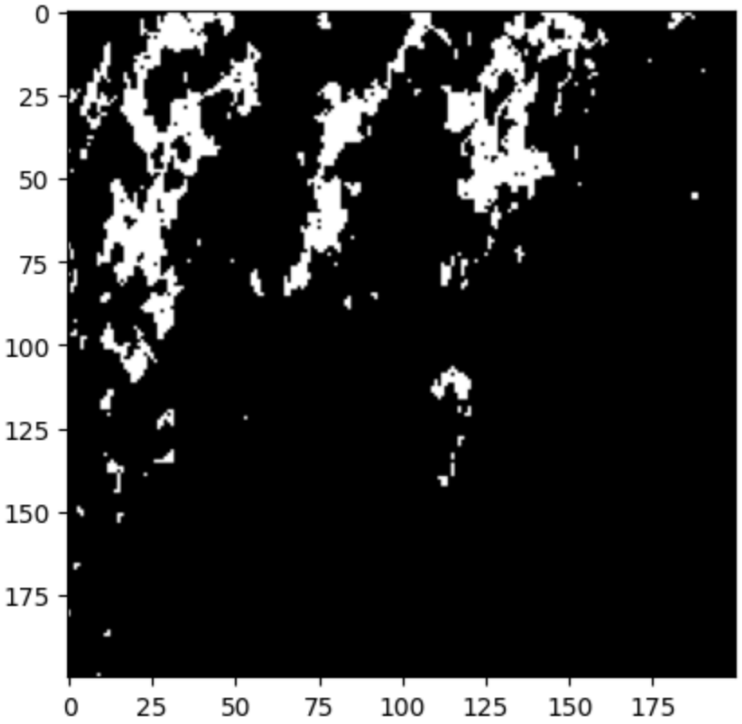


Prediction using UNET

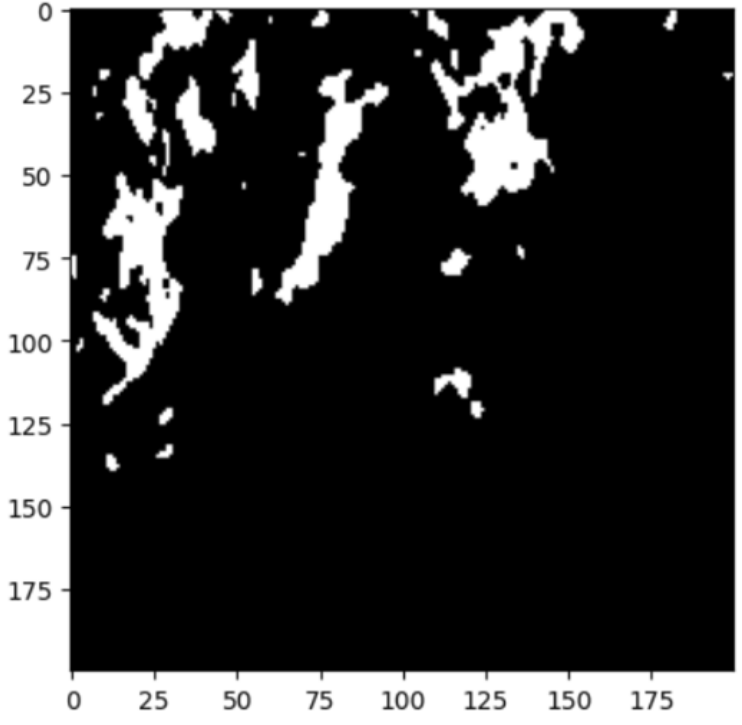


Results

Entire Area as Target



Prediction using R2U-Net



Discussion and Conclusion

- Both models performed well with R2U-Net doing slightly better.
- UNet ; RMSE~0.2533 for the test data and RMSE~ 0.6127 for validation.
- R2U-Net ; RMSE~0.2215 for the test data and RMSE~0.3197 for validation. Also, it was better in capturing some of the small LS.
- The main challenge we faced was overfitting.
- Imbalanced dataset.
- Having more data would perhaps make the training better.
- Selecting the appropriate number of channels played a key role in the accuracy of our output for the models.

Thank You

Questions?